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Identification and Mitigation of NLOS based on Channel Information Rules for Indoor UWB Localization

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Identification and Mitigation of NLOS based on Channel Information Rules for Indoor UWB Localization

By

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Identification and Mitigation of NLOS based on Channel Information Rules for Indoor UWB Localization

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ABSTRACT

Indoor localization is an emerging technology that can be utilized for developing products and services for commercial usage, public safety, military applications and so forth. Commercially it can be applied to track children, people with special needs, help navigate blind people, locate equipment, mobile robots, etc. The objective of this thesis is to enable an indoor mobile vehicle to determine its location and thereby making it capable of autonomous localization under Non-light of sight (NLOS) conditions. The solution developed is based on Ultra Wideband (UWB) based Indoor Positioning System (IPS) in the building. The proposed method increases robustness, scalability, and accuracy of location.

The out of the box system of DecaWave TREK1000 provides tag tracking features but has no method to detect and mitigate location inaccuracies due to the multipath effect from physical obstacles found in an indoor environment. This NLOS condition causes ranges to be positively biased, hence the wrong location is reported. Our approach to deal with the NLOS problem is based on the use of Rules Classifier, which is based on channel information. Once better range readings are achieved, approximate location is calculated based on Time of Flight (TOF). Moreover, the proposed rule based IPS can be easily implemented on hardware due to the low complexity. The measurement results, which was obtained using the proposed mitigation algorithm, show considerable improvements in the accuracy of the location estimation which can be used in different IPS applications requiring centimeter level precision. The performance of the proposed algorithm is evaluated experimentally using an indoor positioning platform in a laboratory environment, and is shown to be significantly better than conventional approaches. The maximum positioning error is reduced to ± 15 *cm* for NLOS using both an offline and real time tracking algorithm extended from the proposed approach.

DEDICATION

To my Parents

Ramesh & Kiran Tank,

&

To my Sisters

Hiral Mistry & Krishna Tank

&

To my love, Umesh Shah

&

To my Friends & Family

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ACRONYMS	DEFINITION
AP	Access Point
AOA	Angle of Arrival
BBB	BeagleBone Black
CIR	Channel Impulse Response
DS-TWR	Double-Sided Two-Way Ranging
ECC	European Communications Committee
EKF	Extended Kalman Filter
FCC	Federal Communications Commission
GHz	Gigahertz
GPS	Global Positioning System
I2C	Inter-Integrated Circuit
IEEE	Institute of Electrical and Electronics Engineers
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IPS	Indoor Positioning System
IR	Impulse Radio
ISM	Industrial, Scientific and Medical
LOS	Line Of Sight
Mbps	Megabits Per Second
MEMS	Micro Electro Mechanical System
NIS	Normalized Innovation Squared
NLOS	Non Line of Sight
PRF	Pulse Repetition Frequency

RFID	Radio Frequency Identification
RMS	Root Mean Square
ROS	Robot Operating System
RSSI	Received Signal Strength Indicator
RTLS	Real Time Locating System
SDS-TWR	Symmetric Double-Sided Two-Way Ranging
SIG	Special Interest Group
SPI	Serial Peripheral Interface
SS-TWR	Single-Sided Two-Way Ranging
TOA	Time Of Arrival
TOF	Time Of Flight
TWR	Two Way Ranging
UART	Universal Asynchronous Receiver/Transmitter
USB	Universal Serial Bus
UWB	Ultra Wideband
V	Volt
WLAN	Wireless Local Area Network
WPAN	Wireless Personal Area Network

Chapter 1

Introduction

1.1 Background

Localization of objects has been of significant importance for the community for a long time. Nowadays, Global Positioning System (GPS) can take us within meters of accuracy. When finding the position of a building, this level of precision is satisfactory. However, with regards to localization or navigation of objects indoors, when there is need to know more accurately where inside of a building something is positioned, it is not sufficient. The location of an object with such accuracy could, for example, be useful in large warehouses or emergency situations. Typical applications of Indoor Positioning Systems (IPS) are navigation in stores and targeted advertising, the organization of guided tours in museums, tracking the assets and personnel in hospitals, airports and cargo terminals, warehouses. There are some technical methods of wirelessly tracking down people, equipment, and goods. Wireless position information might be used not only to provide application or location based services but also as support for radio resource management (mobility support, adaptive channel assignment) within the own systems. There are several algorithmic approaches to wireless position and tracking with various degrees of precision and accuracy [1–6]. In general, positioning accuracy is highly dependent on the signal parameters and especially on the wireless technology used, since it determines the quality of the estimation of those parameters.

1.2 Motivation

Position and tracking systems working on Wireless Local Area Network (WLAN), Bluetooth, ZigBee or Radio Frequency Identification (RFID) are usually based on Received Signal Strength Indicator (RSSI) estimation, and their accuracy is low [7]. One of the most promising technologies addressed to position and tracking systems is Ultra Wide Band (UWB) [8]. UWB combines remarkable features concerning size and power consumption, providing high accuracy on distance estimation and allowing simultaneous location and data transmission with high data rates. Impulse Radio (IR) UWB communication systems are based on the transmission of very short duration pulses, which originates very high bandwidth signals. The downfall of UWB based systems employing Time of Arrival (TOA), is that they suffer from location inaccuracies due to the multipath effect from physical obstacles found in an indoor environment [9]. These obstacles cause a scenario called Non Line-of-Sight (NLOS) to occur between the transmitter and receiver. Because of NLOS, the calculated distance between the transmitter and receiver will be biased, and the end application of those systems will be affected. Also, NLOS inaccuracy varies and depends on the size of the obstacle and the material of the obstacle. Therefore, it is necessary that NLOS identification and mitigation techniques are introduced to improve the accuracy of indoor localization. By identifying and mitigating the inaccuracies caused by NLOS, positioning system based on UWB or any other system which suffer from this phenomenon, can be made more robust while maintaining accuracy.

1.3 Goals

UWB based IPS can give an accuracy of location in centimeters for particularly any type of systems, due to large bandwidth and high data transmission capabilities. For mobile vehicle, centimeter level accuracy for operations is must otherwise vehicle will move causing accidents on the way. As indoor environment can not be perfect as always, these severe environments may cause the NLOS for signals, which introduces positive bias in ranging estimation of the UWB transmitter and receiver and degrades the overall position estimation of the system. First, by identifying the NLOS ranges and then applying some mitigation technique for that NLOS ranges, we can reduce this bias in the estimation and get a more accurate position. The identification and mitigation algorithm presented in this research is based on Channel Information Rules. These rules are based on the First Path Gain, Rise Time, and Received signal level power of the channel. An anchor is identified as being NLOS by measured power levels and Rise Time, then the rules are applied to mitigate those ranges and we will make the location accurate.

The main goal of this thesis is to design a wireless positioning system for Industrial Mobile Vehicle capable of navigating in indoor environment with the position accuracy of centimeter precision. The goals can be further divided as follows:

1. Test and validate the accuracy of UWB based IPS for LOS and NLOS conditions

2. Design and Implement a robust algorithm for Identification and Mitigation of NLOS ranges of UWB system

1.4 Thesis Contribution

In this thesis, we have developed an in-house UWB ranging system. First for the UWB based IPS, the proposed algorithm will identify and mitigate the calculated NLOS range between a tag and an anchor, which results in an improvement of a tag's coordinates after range processing through trilateration. The identification and mitigation technique used is based on Channel Information Rules. The identification of NLOS is developed and implemented into a real time system using the DecaWave TREK1000 system and does not rely on previously sampled measurements. We are using DecaWave's TREK1000 as our IPS. Data for the simulation is acquired using real world experimental data from the TREK1000 system in a laboratory environment. In this research, the experiments use three anchors and one tag to perform simulations and practical implementations for demonstrating the validity and practicality of the solution proposed. All implementations are done using the embedded platform of Beagle Bone Black(BBB) to which UWB tag is connected through Universal Serial Bus (USB). All the anchors are flashed once to give appropriate output, and they are running on USB power. The tag is also flashed once and connected to BBB. BBB has WiFi communication through which we can publish the location of the vehicle to the far away from Master computer's application, and we can locate the vehicle from there only. There is no physical connection between anchors or tag nor between BBB to Master PC. All wireless and autonomous vehicle with centimeter level accuracy! The main contribution of this thesis is

- Mitigation of NLOS ranges with $\pm 15\ cm$ accuracy to the true range
- Designing and Implementing the identification and mitigation algorithm which depends on parameters extracted from the signal
- Do not need any extra hardware for Implementation
- A complete and scalable indoor positioning system for a mobile vehicle with improved position in NLOS situations

Some of the similar results obtained from experimentation using the system have been previously presented in [3], [10] and in [6], including a description of the main system characteristics from a system level point of view.

1.5 Organization Of Thesis

The outline of the thesis is as follows. Chapter 2 details the related work in the field of the Indoor positioning system and the UWB NLOS range identification and mitigation techniques with literature review. After that, in Chapter 3, the standards applicable to the development of this system and implementation methodology and major challenges faced during implementation, are discussed. In Chapter 4, the experimental setup used to test the system and the test results when using the system in a real world implementation with the TREK1000 hardware is presented. Finally, in Chapter 5, conclusions regarding the work are drawn.

Chapter 2

Literature Review

2.1 Background

Real time locating system (RTLS) is a system that can be used to track the position of an object inside a coverage area with the smallest time delay. It has been a dynamic research field in which a significant part of the research concentrates on using existing technologies to address the issue of location estimation. Different applications may require different types of positioning technologies that fit their needs and constraints. For instance, GPS is a technology that is suitable and efficient for outdoor spaces rather than indoor spaces because satellite radio signals cannot penetrate solid walls and obstacles [7, 9, 11, 12]. Consequently, there is significant research aimed at finding a substitute for satellite positioning which satisfies demands of indoor positioning applications. IPSs determine the location of an object in an enclosed space continuously and in real-time. IPSs utilize numerous positioning approaches, which vary greatly in terms of accuracy, cost, precision, technology, scalability, robustness, and security [7, 12]. Due to the increased demand for precise indoor location, a number of methods for positioning with various sensors and different degrees of precision were proposed over the past few decades. It has become an active research area in which different solutions have been proposed [1, 2, 4–6].

2.2 Overview of Indoor Positioning System

Indoor positioning [11] can be defined as any system that provides a precise location inside of a closed structure, such as an airport, underground subways, shopping malls, parking garages, warehouses, and university campuses. By the complex nature of indoor environments, the development of an indoor localization technique is always associated with a set of challenges [12]. Challenges indoor environments have,

- Multipath impact from signals' reflection and attenuation by walls and furniture
- High attenuation and signal scattering due to greater density of obstacles
- Fast temporal changes due to the presence of people and opening of doors
- Non Line of Sight (NLOS) conditions
- High demand for precision and accuracy

For precise location estimation, a positioning system must be able to deal with these challenges.

2.2.1 Application of Indoor Positioning Systems

Indoor positioning has numerous applications such as locating devices through structures, guiding visitors in historical centers, tracking expensive equipment in inventory, tracking children in crowded places, providing indoor navigation systems for blind and visually impaired individuals, and finding an emergency exit in a smoky environment, etc. IPSs for different applications may require different quality attributes, and thus IPSs should be carefully selected to meet the requirements of the application. Indoor location-based services are an important application of ubiquitous indoor computing. Accurate location estimation is a critical requirement for IPS. Different technologies used for these IPSs and how the position is calculated by these technologies and the characteristics of them are discussed in detail in the following sections.

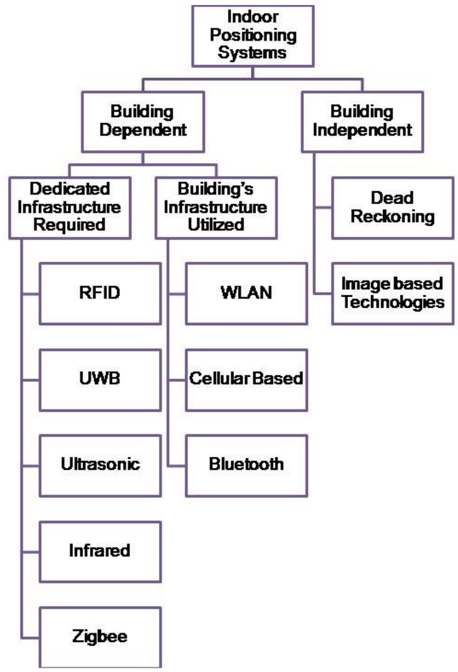

Figure 2.1: Classification of Different Indoor Positioning Systems

2.2.2 Indoor Positioning Technologies

Classification of IPSs based on the infrastructure of the system that uses them is shown in Figure 2.1. We classify IPSs into two main types: Building Dependent and Building Independent. Systems that rely on the building that they operate in refers to Building dependent IPSs. They depend either on an existing technology in the building or on the map and structure of the building. Building dependent IPSs can be further divided into two major types: IPSs that require dedicated infrastructure and IPSs that utilize the building's infrastructure. The need for dedicated infrastructure is determined according to the general structure of most current buildings; e.g., most buildings contain WiFi while almost none contains Zigbee. IPSs that require dedicated infrastructure is (1) Radio frequency that is either RFID or UWB; (2) Infrared; (3) Ultrasonic; (4) Zigbee; and (5) Laser. IPSs that utilize the buildings infrastructure are (1) Wireless Local Area Network (WLAN); (2) Cellular based; and (3) Bluetooth. On the other hand, the building independent systems do not require any special hardware in a building, for example, Dead Reckoning and Image based technologies. In dead reckoning, an object can determine its current location by knowing its past location, its velocity and the direction in which it is moving [13]. Image based technologies mainly rely on a camera (e.g., sensor and image processing) and they can be building independent or building dependent. Image based building dependent technologies depend on special signs in a building or a map of the building. Image based building independent technologies do not require information about the building's map or any special signs. Further detail of these technologies is given in the following section.

Radio Frequency Identification (RFID):

Radio frequency Identification utilizes radio waves to transmit the identity of an object (or individual) wirelessly. RFID technology is most commonly used to automatically identify objects in large systems. It is based on exchanging different frequencies of radio waves between two main components: readers and tags. Tags emit radio signals that are received by readers and vice versa. Both tags and readers use predefined radio frequencies and protocols to send and receive data between them. Tags are attached to all the objects that need to be tracked. The tags comprise of a microchip which can usually store up to 2 kilobytes of data, and a radio antenna. There are two types of tags, active tags and passive tags. On the other hand, an RFID reader consists of different components, including an antenna, transceiver, power supply, processor, and interface, in order to connect to a server [9]. Although different positioning methods can be used with RFID, proximity is the most used one and it senses the presence of RFID tags rather than the exact position [9]. Therefore the accuracy of an RFID system is directly related to the density of tag deployment and reading ranges. Some long range active RFID systems can also use signal strength information to improve the localization accuracy. The main application of RFID location systems is route guidance for pedestrians [4].

ZigBee:

ZigBee is an emerging wireless technology standard which provides solution for short and medium range communications due to its numerous benefits [14]. It is mainly designed for applications which require low power consumption but do not require large data throughput. The signal range coverage of a ZigBee in indoor environments is typically 20 m to 30 m. Distance calculation between two ZigBee nodes is usually carried out from RSSI values. ZigBee is open to interference from a wide range of signal types using the same frequency which can disrupt radio communication because it operates in the unlicensed Industrial, Scientific and Medical (ISM) bands. Hu et al. [15], employed a ZigBee based localization algorithm for indoor environments. Alongside, Fernandez et al. [16], proposed an approach to enhance the position determination in an indoor location system based on the power levels (RSSI) of an ad hoc ZigBee network.

Ultra Wideband (UWB):

Ultra Wideband transmits a signal over multiple bands of frequencies simultaneously, from 3.1 to 10.6 GHz. It is a radio technology for short range, high bandwidth communication holding the properties of strong multipath resistance. This allows UWB transmitters to transmit large amounts of data while consuming little transmit energy [17]. There is widespread use of UWB in a variety of localization applications requiring higher accuracy in centimeter than achievable through conventional wireless technologies (e.g.,RFID,WLAN, etc.) [8]. Depending on the positioning technique, the Angle of Arrival (AOA), the signal strength (SS), or time delay information can be used to determine the location of an object. Detail discussion on UWB is in following section of this chapter.

Bluetooth:

Bluetooth is a wireless standard for Wireless Personal Area Networks (WPANs). Almost every Wi-Fi enabled devices, such as mobile phone or computer, also has an embedded Bluetooth module. Bluetooth operates in the 2.4 GHz ISM band. The benefit of using

Bluetooth for exchanging information between devices is that this technology is of high security, low cost, low power, and small size. Each Bluetooth tag has a unique ID, which can be used for locating the Bluetooth tag. The Bluetooth Special Interest Group (SIG) which manages Bluetooth, include a local group that investigates the use of Bluetooth wireless technology for positioning [17]. Bluetooth technology commonly uses proximity and RSSI methods to estimate positions [17]. One of the drawbacks of using Bluetooth technology in localization is that, in each location finding, it runs the device discovery procedure, due to this, it significantly increases the localization latency ($10-30$ s) and power consumption as well. That is why Bluetooth device has a latency unsuitable for real time positioning applications. Another disadvantage of a Bluetooth based positioning system is that it can only provide accuracy about from 2 m to 5 m with a delay of about 20 s. Furthermore, the Bluetooth based positioning systems suffer from the drawbacks of the RF localization technique in the complex and changing indoor situations.

Wireless Local Area Network (WLAN):

This midrange WLAN standard, operating in the 2.4 GHz ISM band, has become very popular in public hotspots and enterprise locations during the last few years. With a typical gross bit rate of $11, 54,$ or 108 Megabits per second (Mbps) and a range of $50-100$ m, IEEE 802.11 is currently the dominant local wireless networking standard. It is, therefore, appealing to use an existing WLAN infrastructure for indoor location as well, by adding a location server. For this reason, one of the main advantages of using WiFi localization technique is its cost effectiveness due to the possibility to localize the position of almost every WiFi compatible device without installing extra software. Another advantage of using WLAN is that LOS is not required. The most popular WLAN positioning method is to make use of RSSI, which are easy to extract in IEEE 802.11 networks. The accuracy of typical WLAN positioning systems using RSSI is approximately 3 to 30 m, with an update rate in the range of few seconds, but it can be improved by dense deployment of wireless routers or by integrating other technologies, and recent results talk about $3-5\ m$ accuracy [8]. In addition to accuracy, many challenging issues in the WLAN localization technology are important. Among these, power consumption is the main. In fact, since mobile devices are usually small and have battery power constraints, a challenging issue is how to reduce the power required for localization. Another WLAN limitation is the signal attenuation of the static environment like wall, movement of furniture, and doors.

Dead Reckoning:

Dead reckoning is the process of estimating known current position based on last known position and incrementing that position based on known or estimated velocity or acceleration. An Inertial Navigation System (INS) which provides very accurate directional information uses dead reckoning and is very widely applied [13]. One of the disadvantages of dead reckoning is that the inaccuracy of the process is cumulative, so the deviation in the position fix grows with time. Research has been carried out in indoor localization using dead reckoning in [13].

Summary of IPS:

In order to choose the most suitable technology or a combination of them for the design and implementation of an IPS, a comparison among the alternative technologies is very useful. In Table 2.1, some parameters have been selected for the comparison, i.e., typical operative environment, coverage, complexity, cost and accuracy. The values of these parameters have a purely indicative meaning as the real values, which depend on many factors, should be evaluated case by case.

Table 2.1: Comparison of Different Infrastructure based technologies used for IPS

			Parameters			
Technology	Operating Frequency	Environment	Coverage (m)	Complexity	Cost	Accuracy
RFID	125-134 KHz, 860-960 MHz	Indoor	$1-10$	Low	Medium	$1-2$ (m)
Zigbee	2.4 GHz	Indoor	$20-30$	Low	Low	$3-5$ (m)
UWB	3.1-10.6 GHz	Indoor/Outdoor	$50-60$	Low	Medium/Low	$20-30$ (cm)
Bluetooth	2.4 GHz	Indoor/Outdoor	$1-30$	Low	Low	$2-5$ (m)
WLAN	2.4-5 GHz	Indoor/Outdoor	$20-50$	Low	Medium/Low	$3-5$ (m)

2.2.3 Why UWB?

Given the overview of different IPSs, for precise location estimation, a positioning system should be able to fulfill some of the common and important requirements of different IPS:

- Operate in complex indoor environments without interference with other radio signals
- Operate in a satisfactory coverage area without use of repeaters of the system
- Provide less configuration and computational complexity
- Provide centimeter level accuracy
- Be cost effective

Furthermore, due to the U.S. Federal Communications Commission's (FCC's) recent allowance for the use of unlicensed UWB communications, civilian applications have been studied and explored for UWB intensively worldwide. Since UWB spans over such a large range of frequencies, the FCC decided it must regulate UWB such that it does not interfere with other communications standards within the 3.1 to 10.6 GHz band. In order to prevent interference with other IEEE wireless standards, the FCC decided that the maximum transmit power UWB can produce is $-41.3\ dBm/MHz$. Figure 2.2 shows a chart that compares various existing wireless standards in terms of bandwidth and signal power. In Figure 2.2, it is seen that UWB overlaps with the IEEE WLAN 802.11a spectrum. For this reason, it was required that the FCC limit the transmit power of UWB in order to not interfere with existing WLAN standards.

Many infrastructure-based indoor positioning technologies such as RFID, WLAN, Zigbee, even Bluetooth are inefficient considering many factors as compared in table 2.1. But depending on requirements of different applications this comparison will vary. For accurate

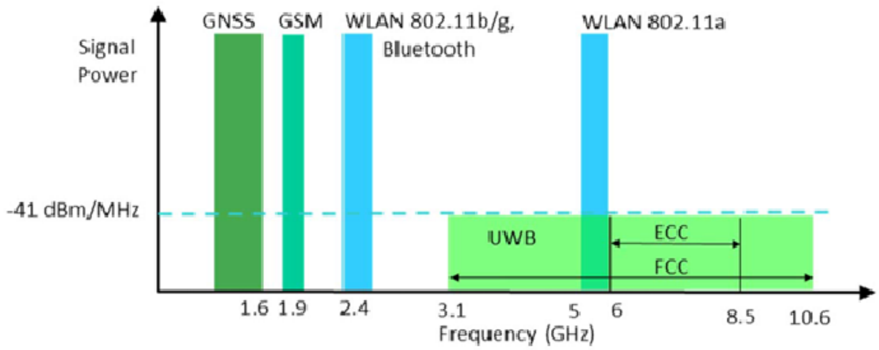

Figure 2.2: Signal Power vs Frequency of different Wireless standards [18]

location value in case of tracking expensive equipment in inventory, centimeter level accuracy is must for mobile vehicle. UWB provides centimeter level accuracy for this type of applications. All of these factors and in addition to that, UWB satisfy most of the important requirements of any IPS, making UWB a good choice for indoor positioning applications. Hence, in the recent years UWB based indoor positioning systems and new algorithms to improve UWB positioning performance is emerging as an active research area [3–6, 8, 10]. Indoor positioning using the UWB spectrum has been adopted by the market by companies such as DecaWave, UbiSense and Time Domain.

2.3 Indoor Positioning Techniques

We have classified IPS based on different technologies they use or dependent on. How this technology calculate the position of a node is also an important aspect for any IPS. Positioning a node in a wireless system involves the collection of position information from radio signals traveling between the target node and a number of reference nodes. Depending on the positioning technique, the AOA, the signal strength, or time delay information one can determine the position of a node [5, 7, 9, 12, 17]. The AOA technique measures the angles between a given node and a number of reference nodes to estimate the location, while the SS and time based approaches estimate the distance between nodes by measuring the energy and the travel time of the received signal, respectively.

2.3.1 Angle of Arrival (AOA)

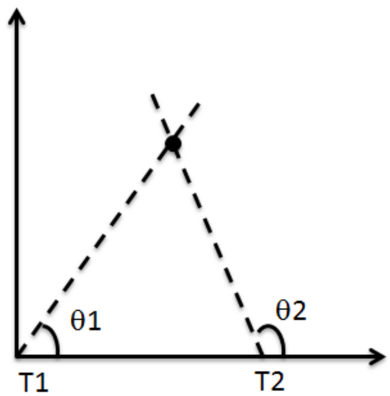

Figure 2.3: AOA positioning Technique

In AOA technique, the angle of a received signal from a known transmitting node is obtain, in order to calculate the position of an object. The angle of signal can be determined if the transmitter and receiver devices use directional antennas and the signal transmitted only under LOS conditions. To determine the position of a node in a two-dimensional (2-D) space, it is sufficient to measure the angles of the straight lines that connect the node and two reference nodes, as shown in Figure 2.3. For the application of indoor positioning, the main disadvantage of AOA is that in NLOS conditions the angle of the incoming signal may be incorrect due to signal reflections (multipath) from obstacles in the room. Signal reflections will cause an incorrect angle to be calculated. A room with many metallic objects can impact the performance of AOA since metallic objects severely attenuate the signal and reflect waves.

Suppose (x_0, y_0) and (x_i, y_i) represent the locations of the node and the ith transmitter respectively. Assuming $\theta 1$ and $\theta 2$, represents the arrival of angles detected by the antenna of T1 and T2, respectively. Then by solving the nonlinear equation 2.1 given below,

$$\tan\theta = (y_i - y_0)/(x_i - x_0),\ i = 1,2 \tag{2.1}$$

we can get estimated position of the node. The first advantage of the AOA technique is that there is no need for the expensive time synchronization since the AOA of one transmitter-receiver pair is obtained using the (pseudo)range differences of multiple antenna components at the same receiver. However, this method causes higher cost, complexity and power consumption compared with other methods.

2.3.2 Time of Arrival (TOA) / Time of Flight (TOF)

The time of arrival of the received signal is the most important parameter in an accurate indoor positioning system. The time of arrival estimation allows the measurement of distance in an indoor positioning system. In the TOA method the anchor nodes use a trilateration to localize the target node. The anchor nodes can be static or dynamic. It is assumed that the positions of all static anchor nodes are known. The principle of TOA / TOF is based on measuring the absolute travel time of a signal from a transmitter to a receiver. TOA requires both the transmitter and receiver to have a synchronized time base to accurately timestamp packets, as even one nanosecond error in synchronization translates into a distance error of 30 cm if radio frequency signals are used.

If the distance of the node to the ith transmitter is d_i , (i = 1,2,3), as shown in Fig. 2.4, the node must be in a circle. The center of the circle is the ith transmitter and the radius of the circle is d_i. Then the intersection of the circles is the position of the node. Suppose (x_0, y_0) and (x_i, y_i) represent the locations of the node and the ith Transmitter respectively. They should satisfy formula 2.2:

$$(x_i - x_0)^2 + (y_i - y_0)^2 = d_i^2,\ i = 1,2,3 \tag{2.2}$$

The advantage of the TOA method is that there are already well developed timing based multiple access schemes, which allow the high accurate TOA estimation. The disadvan-

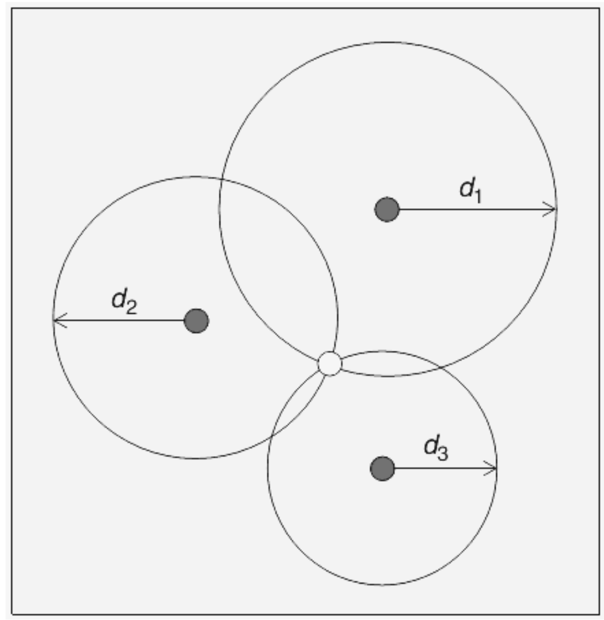

Figure 2.4: TOA positioning technique

tages of the TOA is that all the units need to be synchronized with each other in a system but synchronization is difficult and expensive to use for wireless radio systems. We are using two way ranging TOA technique to measure the position of the mobile vehicle in this thesis considering the synchronization of the nodes. More on two way TOA is discussed later.

2.3.3 Time Difference of Arrival (TDOA)

TDOA works by calculating the cross correlation between signals arriving at nodes. All nodes must be time synchronized as well. TOA and the cross correlation of the signals create hyperbolas that intersect at a specific point. TDOA allows transmitter nodes to continuously broadcast a range signal and not have to interact with the receiver nodes. This allows for many receiver nodes to be deployed since they do not communicate with transmitter nodes but instead only listen to them. This technique is applied to GPS systems found today. That is why millions of users are able to simultaneously use GPS at the same time.

Let $d_{21} = d_2 - d_1$ is the distance difference between the node to transmitters T1 and T2,

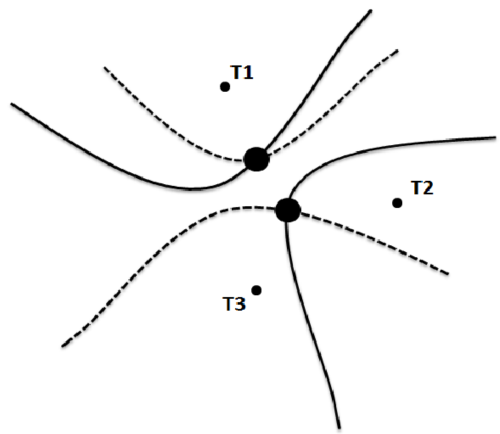

Figure 2.5: TDOA positioning technique

as shown in Fig. 2.5, the node must be located in the hyperbola which focuses on these two transmitter. The node also locates in the hyperbolas which focus on T1 and T3 in a similar way. Then the intersections of two hyperbolas are likely to be the location of the node. That is, the locations of the node and transmitters must meet the formula 2.3.

$$d_{i1}^2 = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} - \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2},\ i = 2,3 \tag{2.3}$$

There are two solutions obtaining from equation 2.3, which corresponding to the two intersections of two hyperbolas. However, only one intersection is representative of the real location of the node, it needs some prior knowledge to distinguish true solution to eliminate the position ambiguity. The drawback of this system is that that crystal oscillator on both the transmitter and the receiver must be perfectly aligned, which is never the case. Also, TDOA is less accurate than the TOA system if they are using the same system geometry. For this reason, two way TOA ranging is used.

2.3.4 Received Signal Strength (RSS)

This technique estimates the position according to the Received Signal Strength (generally refers to radio frequency signal). RSS localization technique can be divided into two steps: Propagation model method and Fingerprinting method. Propagation model method, needs to establish a model between RSS and the distance. Generally, the larger of the RSS values, the closer from the Access Point (AP). In the open free space, attenuation of signal strength is inversely proportional to the distance from AP. But the indoor environment is very complex, the furniture, equipments, windows and doors may cause multiparty propagation, such as reflection, refraction, diffraction. And different structure of the obstacles may cause the different attenuation coefficient for RF signals. So the establishment of accurate indoor propagation model is very difficult.

Fingerprint method is the most feasible solution for RSS based indoor localization and works by mapping the observed signal strength of fixed routers placed in the indoor environment into a database. The basic design of the fingerprinting method can be divided in offline stage and online stage. During the offline stage, RSS is collected at sampling locations to build the radio map for the specific environment. During the online stage, the physical location of the client can be estimated by comparing the measured RSS with the stored RSS values. RSS fingerprinting is commonly used in systems employing WLAN based indoor positioning. RSS fingerprinting is not feasible in practice due to fingerprint maps required to be created. To create a fingerprint map for every possible WLAN access point, for every room, would require extensive setup prior to a system being able to run.

2.4 Ultra Wideband

UWB was first developed in 1960 for radar applications. This technology has become the focus of developments more recently for both wireless data communication and RTLS. UWB operates by transmitting a series of signals as narrow pulses in the time domain, which in turn spreads information over a very large spectral bandwidth, typically from 3.1 to 10.6 GHz. The pulse duration is very short, varying between some picoseconds and nanoseconds. This communication technology is especially suitable for localization applications, as it allows ranging with centimetric accuracy. Characteristics of UWB signals offer a wealth of advantages for localization applications. Since UWB signals have very large bandwidths and the pulse duration is very short, it is possible to have extremely accurate location estimates. The absence of carrier frequency and the low power spectral density tend to reduce interference to other systems. Moreover, thanks to these characteristics direct line of sight can be more easily separated from multipath components, undesirable in localization applications. Therefore UWB is foreseen as one of the most promising technologies for indoor localization.

A major advantage of using UWB for distance measurements is that large bandwidth translates into a high resolution in time and consequently in range. The achievable range resolution rr can be approximated with,

$$rr = \frac{v}{2B} \tag{2.4}$$

where v is the speed of the wave front and B is the bandwidth. E.g. for the FCC band and propagation in free space (assuming speed of light with $v = c_0$), it is $rr \approx 0.5c_0/7.5\ GHz = 2\ cm$, respectively 6 cm for the ECC band at bandwidth B = 2.5 GHz.

There are essentially two UWB signaling families, one based on continuous transmission of multi-carrier waves and the other based on the transmission of short baseband pulses. In this thesis we shall concentrate on the last one, which is commonly referred to in the literature as Impulse Radio UWB.

Continuous Waves

Within the frequency band, different frequencies are sequentially used by stepping or sweeping (i.e. frequency modulation). The signal is analyzed in the frequency domain resulting in low time resolution which is unfavorable for dynamic real time applications. Continuous waves allow for precise ranging, but cannot be used for small devices such as a smart phone because such technology requires large antennas. If the frequency range is very wide, a large physical size of the antenna is necessary to achieve sufficient antenna efficiency.

Impulse Radio (IR)

The UWB-IR is simply structured and can be used for fast distance measurements. The duration of the pulses is in the order of nanoseconds or even less. Compared to continuous waves, ultrashort pulses are less likely to interfere with signals traveling other paths allowing for better resolution of the LOS path and therefore evoking robustness against multipath. Since the radios have to be powered for a short time only before and during pulse generation, UWB-IR has a low power consumption compared to other UWB techniques.

2.4.1 UWB Ranging Techniques

UWB ranging techniques include AOA, TOA and Two Way Ranging (TWR).

Angle Of Arrival (AOA)

As mentioned in subsection of positioning techniques in chapter 2 above, we conclude that AOA approach is not suited to UWB positioning for the following reasons. First, use of antenna arrays increases the system cost, annulling the main advantage of a UWB radio equipped with low cost transceivers. More importantly, due to the large bandwidth of a UWB signal, the number of paths may be very large, especially in indoor environments. Therefore, accurate angle estimation becomes very challenging due to scattering from objects in the environment. Moreover, time based approaches can provide very precise location estimates, and therefore they are better motivated for UWB over the more costly AOA based techniques.

Time of Arrival (TOA)

TOA is particularly difficult to apply in indoor environments where multipath conditions are common, because the autocorrelation peak in the signal referring to the LOS beam may not be resolved. The usage of a wider frequency band is a way to address this problem. The IEEE 802.15.4a Task Group specifications define, among others, a ranging and therewith localization protocol which is based on a two way TOA estimation scheme [19]. The procedure enables a mobile device to sequentially estimate its distance to other devices without the need of synchronization between these reference devices, as required for example in the case of Time Difference Of Arrival (TDOA) methods. Also, because of the real distances instead of distance differences estimated, the number of reference points necessary for a 3D position fix is only three compared to four in case of TDOA localization. For practical system considerations, this reduction of complexity can be eminent, as installation costs are considerably lower because of unneeded synchronization cabling and fewer reference points needs. This concept is applied with the RTLS concept as defined in the international standard ISO/IEC FCD 24730-5.

If the anchor and tag are not time synchronized in TOA, two way ranging is applied, such as in the DecaWave TREK1000 system, where the ranging message is sent from the anchor to the tag, then back to the anchor to precisely calculate the signal time of flight.

2.4.2 Two Way Ranging (TWR)

Two way ranging (TWR) is another way of ranging accomplished by the use of two transceivers. When employing TWR, the TOF is calculated by using the reply time(s), which is the time elapsed between second device receiving a message until a reply is sent, and the round trip time(s), which is the time elapsed between first device sending a message until a response is received. By using TWR the need of synchronized clocks is eliminated since both the round trip time(s) and the reply time(s) can be calculated separately using timestamps derived from one device. Several implementations of TWR between two nodes are described below.

Single Sided Two Way Ranging (SSTWR)

Single sided two way ranging (SSTWR) involves a simple measurement of the round trip delay of a single message from one node to another and a response sent back to the original node. Single sided TWR is a ranging scheme where Device A sends a message to Device B, which sends a reply message back to Device A. Figure 2.6 illustrates a single-sided TWR scheme. When single sided TWR is used, the TOF can be calculated by using Equation 2.5 where T_{prop} denotes the TOF, T_{round} denotes the round trip time and T_{reply} denotes the

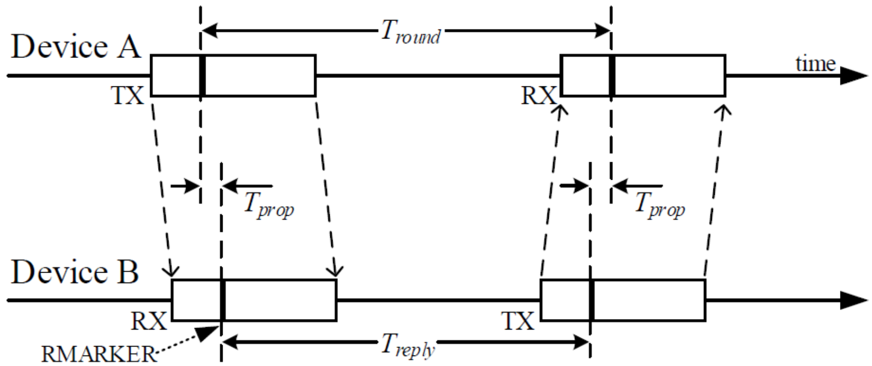

Figure 2.6: Single sided TWR [20]

reply time.

$$T_{prop} = \frac{T_{round} - T_{reply}}{2} \tag{2.5}$$

Double Sided Two Way Ranging (DSTWR)

Double sided two way ranging (DSTWR), is an expansion of the basic single sided TWR in which two round trip time measurements are used and combined to give a time of flight result which has a reduced error even for quite long response delays.

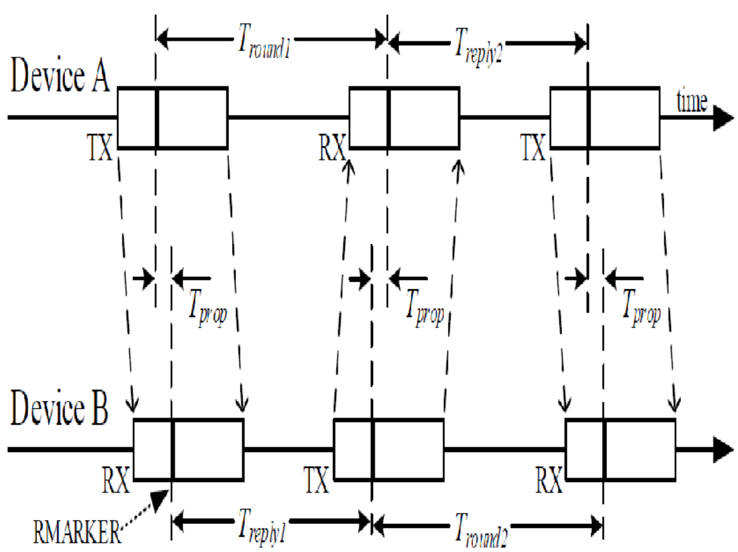

Figure 2.7: Symmetrical Double sided TWR [20]

Symmetrical Double Sided Two Way Ranging (SDSTWR)

From DW1000 documentation [20], symmetrical double sided TWR is a method described in Figure 2.7, where T_{prop} denotes the TOF, T_{round1} and T_{round2} denotes the round trip times and T_{reply1} and T_{reply2} denotes the reply times. By restraining T_{reply1} and T_{reply2} to be equal, T_{prop} can be calculated by using Equation 2.6. Symmetrical double sided TWR has the restriction that T_{reply1} and T_{reply2} has to be equal. Double sided TWR in general gives more stable results compared to single sided TWR by using more measurements and deriving T_{prop} as an average of three transmissions as opposed to single sided TWR where only two transmissions takes place.

$$T_{prop} = \frac{T_{round1} - T_{reply1} + T_{round2} - T_{reply2}}{4} \tag{2.6}$$

DecaWave TREK1000 device employ this Symmetric Double Sided TWR scheme in their DW1000 transceiver chip.

2.5 State Of the Art

This section discusses related positioning systems for indoor environments. The center of attention will be localization accuracy, precision and mitigation techniques. There are many high accuracy RF system been researched and developed recently.

In [2], Evennou and et al. uses WiFi 802.15.4a signal to perform positioning in indoor environments. The location technique is based on the measurement of the received signal strength (RSS) and the well known fingerprinting method. To build the database for this kind of system, is time consuming and complex to implement for large areas or handheld devices. They are reducing the signal fluctuations error by using particle filter and achieving 1.86 m accuracy compared to the only WiFi accuracy results of 3.32 m. They are fusing the system with INS using Particle Filter as well for better accuracy, but localization accuracy they are getting is still 1.53 m while moving at 1 m/s.

With regard to wireless localization that requires infrastructure, WLAN based localization is typically preferable due to the fact that it is ubiquitous. However, TOA ranging with WLAN has lower accuracy than IR-UWB because of the lower channel bandwidth. Although recent standards like 802.11ac and 802.11ad have wider channels than 802.11g/n, making the localization accuracy somewhat similar to IR-UWB (meters or tens of centimeters versus centimeters), it is still not possible to attain the same ranging accuracy as 802.15.4a with these technologies. This is partly attributed to the fact that IR-UWB uses pulses with picosecond duration for communication, which are resistant to multipath and enable centimeter level accuracy, and the 802.15.4a standard makes provision for ranging and allows access to the channel impulse response (CIR) directly, which is currently not possible with conventional WLAN hardware since ranging was not part of the 802.11 standard when it was originally conceived. However, future standards like 802.11v have built-in TOA functionality but have not been realized commercially yet. Currently, the channel information based techniques for NLOS mitigation discussed in this thesis cannot be directly applied to WLAN, since WLAN commercial-off the-shelf transceivers do not have the capability to log the channel information.

Compared to RSS based solutions, which can typically achieve meter scale accuracy at best, localization based on time based approaches enables accuracy in the centimeter scale, due to IR-UWBs very fine time resolution, and it is thus an attractive proposition for highly accurate localization in industrial environments. Systems that uses IR technique are [3,5,6].

In [3] Renaudin and et al. experimented optimal data fusion of UWB and MEMS for pedestrian navigation. The location estimation based on a geometric processing of UWB signal is illustrated. First, the mathematical modeling of the signals metrics, that is the AOA and the TDOA, are formulated. Then the 3D geometry based mobile location estimation algorithms are presented for different cases of AOA and TDOA. They used the RF and magnetometer measurements collected before the start of the movement, to obtain an estimate of the initial position and included the measurements from UWB in the Extended

Kalman Filter (EKF) that propagates the Pedestrian Dead Reckoning (PDR) algorithm. An EKF has been optimized for the fusion of the observations and complemented with a robust Random Sample Consensus (RANSAC) procedure that mitigates the NLOS UWB propagation. Geometrical configuration drawn by the mobile and the base stations affects the UWB propagation causing them to drift more and hence erroneous range.RANSAC algorithm interpret smoothing data that contain a significant percentage of gross error. It chooses a subset of the data by random sampling and estimates a model for each subset. The number of points in the subset is equal to the number of unknown model parameters, yielding closed form solutions. The robustness of RANSAC is contingent on the existence of at least one subset of data carrying the correct model. The accuracy of fusion is compared with pure inertial location estimation and the accuracy they got is in the range of 1 m.

Mohammadreza Yavari, in his Master's thesis [5], researched in detail, the capability of UWB communication technology for indoor real time positioning. He fused UWB based IPS with IMU using EKF. For Identification of NLOS ranges of UWB, he is using the same concept of Receive Signal Power level and First Path Power Level provided by Decawave. The process noise covariance matrix Q in the fused system is determined by the error variance of the accelerometer measurements in each axis. The measurement noise covariance matrix R is computed by the error variance of the UWB range measurements. For LOS, IMU measurements do not have much effect on covariances hence, a small R in relation to Q is chosen and for NLOS, to trust IMU measurements more by increasing values of R. R is increased 30 times to less trust the UWB measurements. For the fused system, during NLOS conditions, the accuracy achieved is 18.8%of the ground truth position and for LOS, positioning accuracy is decreasing. The system is tested with Line follower robot moving at a speed of 0.16 m/s, carrying Decawave's EVB1000 board and IMU. For testing the existence of robot they are using low power light sensor module along the path. Many supported experiment results are provided.

In [6], Paul and et al. tests for the PDR considering dynamic activities of pedestrian as well. They are testing the spatial location and motion of human with UWB based positioning fused with IMU and Biomechanical device model for measuring the dynamic activities. Biomechanical model fitted on lower body part of human measures velocity and height. The algorithm addressed the outliers occurred because of multipath and NLOS conditions by detecting and weighting them using the Normalized Innovation Squared (NIS) test and processing the available accurate measurements at the root joint (waist) sequentially. The measurement noise covariances automatically scaled by the algorithm for each measurements. To save the computational time, sequential Kalman filter was adopted. Their accuracy significantly depends more on Biomechanical model when there are outliers instead of IMU. The results demonstrated significant improvements in positioning accuracy of pedestrian of less than 13 *cm*.

2.5.1 NLOS Identification and Mitigation

As indoor environments can be complex, there is no single model or algorithm that can account for all of the possible scenarios that an IPS might encounter. Existing Indoor positioning systems that are based solely on RSSI are not very accurate due to multipath fading, and require a premade RSSI fingerprint map to be made prior to being deployed. And building this fingerprint map is time consuming and may not be accurate if single thing is moved in the environment. The UWB based IPS systems are very accurate but the biggest challenge faced when using TOA, is when there is NLOS between a target node and an anchor node. In the case of NLOS, the signal does not take the shortest theoretical path, which eventually leads to a positively biased distance reported by TOA calculation. This positively biased TOA calculation is due to the signal taking multiple paths to reach the receiver. The shortest distance between two points is a straight line and when there is an obstacle between these two points, the signal travels in a nonlinear fashion. NLOS causes the distance reported to always be greater than the LOS distance. Thus, in situations where NLOS conditions occur, the distance reported between an anchor and a tag must always be corrected downwards. As a result there is a need for robust algorithms that have the capability to identify and mitigate those NLOS ranging conditions. In this thesis, we propose a novel, low complexity wireless channel condition estimation algorithm that identifies the condition of the channel. Furthermore, in order to correct an NLOS reported distance, NLOS must first be identified. NLOS Identification is a critical parameter in this research because it enables the ability to only mitigate ranges that are strictly NLOS. This saves processing time and increases the accuracy of location for various applications, such as localization of person or objects or mobile vehicle.

Survey papers [21, 22], reviewed the existing UWB based NLOS mitigation techniques published in the literature for dense environments. They are classifying the NLOS channel identification methods into following three categories: 1) Based on Range estimates, 2) Based on Channel statistics, 3) Based on the map of the building. For NLOS mitigation different approaches are available. The main approaches are Geometric based and Non-Geometric based, hybrid schemes and techniques involving the Kalman filter. Machine learning is also an emerging approach for UWB NLOS mitigation. These different mitigation techniques do have their place and are best used in IPS system where NLOS with more than one anchor is extremely high. A review of several existing NLOS identification/classification and mitigation schemes is provided, and proposed scheme is described, which is based on channel information rules.

Stefano Marano and et. al in [10] studied NLOS identification and mitigation for localization using channel parameters as NLOS identification metrics. A Machine learning approach is implemented by them. Alsindi in [23] goes further and also classifies NLOS by severity. It is classified as being 'hard' or 'soft'. NLOS classification is also an important parameter because it can be used as a way to mitigate NLOS range measurements based on the severity of NLOS.

In [24], Chin-Der Wann and et al., identified the NLOS channel by the standard deviation of range estimates. Due to the positive mean NLOS errors, the standard deviation calculated with sliding window cannot reduce immediately when the situation changes from NLOS to LOS. That is why they used the Kalman filter to smooth the data. Before computing the Kalman gain, the range measurement noise covariance was adjusted using the bias adjusting rule.

In [25], Akgul proposes a hybrid mitigation method where AOA and TOA are used in combination. The paper details the mechanics of the TOA approach in using either the first peak or the strongest peak, both which are affected by NLOS conditions. The paper then explains how AOA assisted error mitigation can assist by selecting paths that are closest to the previous sampling point. The motivation behind proposed AOA assisted error mitigation is that the direct path through TOA can be very weak and might not be selected as the first/strongest path. Using AOA, the potential direct path can be selected using a Least Squared (LS) solution. The results showed that the proposed algorithm performed very close to the actual distance and showed improvement over using the first detected path, which was the NLOS path.

The proposed rule based mitigation algorithm combines the measured ranges and channel information to compute the probability of each channel condition. Since the channel information is already available in the receivers, our algorithm requires little or no additional hardware, no additional transmissions and the computation complexity is low. The algorithm is validated by channel measurement results conducted in an laboratory environment and implemented in real time.

Chapter 3

Description of the Work

3.1 System Model

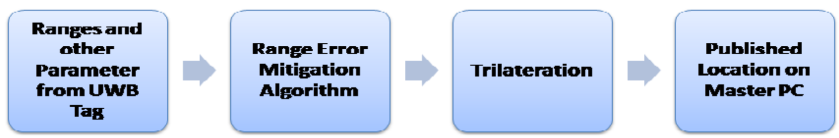

Figure 3.1: System Model

This chapter explains the system development and integration of proposed approach. A system model diagram is shown in Figure 3.1. The out of box TREK1000 system is able to successfully pair with all anchors/tags, and is been flashed to give required ranges and parameters through it's USB port to BBB. When an obstacle is placed between a tag and one or more anchors, the position and reported time of the tag will be inaccurate. This inaccuracy is detected by using the channel information based Rules and biased ranges are mitigated using an algorithm developed. After range processing in mitigation algorithm more accurate location will be generated in trilateration and will publish the location to the Master PC.

3.2 Hardware

This section details specific hardware used for the experiments.

3.2.1 DecaWave

The hardware used in this thesis from DecaWave. DecaWave manufactures two RTLS evaluation kits called EVK1000 and TREK1000. The hardware in both the EVK1000 and TREK1000 kits consists of the same physical hardware, which is the EVB1000 evaluation board as shown in Figure 3.2. The difference between the EVK1000 and TREK1000 evaluation kits is in the firmware and software provided by DecaWave for each kit.

We are utilizing the TREK1000 evaluation kit for our IPS which comes with 4 EVB1000 boards and antenna and necessary USB cables. EVB1000 from DecaWave is an evaluation circuit board incorporating the DW1000 UWB wireless transceiver IC, an ARM type Cortex M3 processor, and a wideband planar omnidirectional antenna. The DW1000 chip is responsible for conveying messages through UWB, getting channel data and decoding/detecting incoming messages. The DW1000 is the heart of the system. The ARM type Cortex M3 processor, STM32F10x is a 32 bit microprocessor that communicates with the DW1000 chip via Serial Peripheral Interface (SPI) transactions and sends out messages to a PC through Universal Serial Bus (USB) or Universal Asynchronous Receiver/Transmitter (UART). SPI, USB, and UART are different types of hardware communication protocols. The manufacturer recommends the two planes of the antennae of two ranging devices to be parallel to each other for best results. The primary reason for choosing the DecaWave hardware is because DecaWave offers low cost products with reasonable LOS accuracy (up to 10cm accuracy), relative to other competing indoor positioning based manufacturers.

The EVK1000 evaluation kit offers firmware to provide a two way ranging distance measurement that displays the distance between two EVK1000 units. It also comes with a premade PC program called DecaRanging that displays Channel Impulse Response (CIR) information along with other diagnostic information from the Accumulator CIR memory

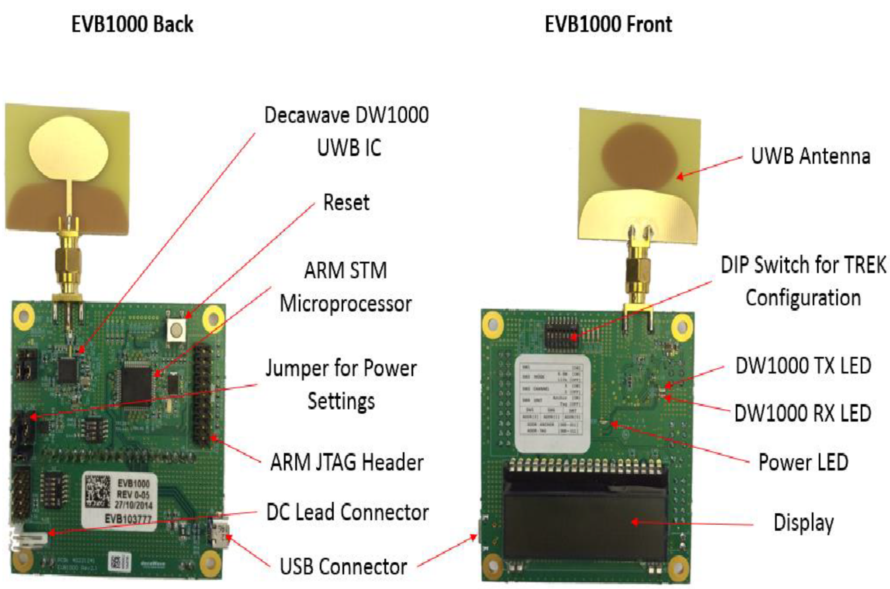

Figure 3.2: EVB1000 by DecaWave [26]

register of DW1000. The TREK1000 system is also capable of getting channel impulse response information but this causes the performance of the system to slow down slightly. But we are accessing the channel impulse response and other diagnostic information without extracting the whole accumulator from the DW1000. Figure 3.3 shows the typical Channel Impulse Response of the received signal extracted from DW1000 accumulator.

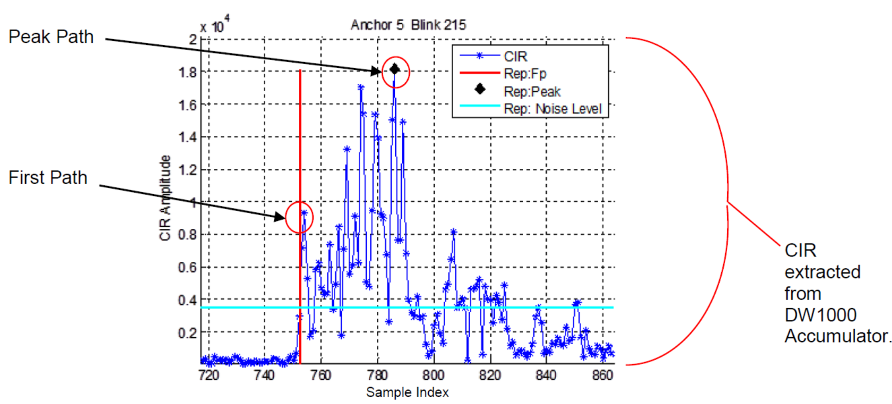

Figure 3.3: A typical accumulator from the DW1000 (*Figure is accepted from One of the DecaWave's Application Notes provided from DecaWave.)

Operating Characteristics of DW1000

The EVB1000 runs all UWB communication from the DW1000 chip on board the unit. The operating abilities of the DW1000 are found in Figure 3.4. There are total of 6 available channels, each with different combinations of center frequency and bandwidth. There are also various preamble codes supporting a 16 or 64 MHz Pulse Repetition Frequency (PRF). The operating abilities of the DW1000 are based on the IEEE 802.15.4 standard. For an in depth knowledge of the UWB operating parameters, the user is referred to the IEEE 802.15.4 standard. The different choice of channels allows multiple independent IPSs to

Channel number	Centre frequency (MHz)	Bandwidth (MHz)	Preamble Codes (16 MHz PRF)	Preamble Codes (64 MHz PRF)
1	3494.4	499.2	1, 2	9, 10, 11, 12
2	3993.6	499.2	3, 4	9, 10, 11, 12
3	4492.8	499.2	5, 6	9, 10, 11, 12
4	3993.6	1331.2*	7, 8	17, 18, 19, 20
5	6489.6	499.2	3, 4	9, 10, 11, 12
7	6489.6	1081.6*	7, 8	17, 18, 19, 20
N.B. For correct operation of the DW1000 the software must take care to only allow selection of those preamble codes appropriate for the configured PRF.				

* The DW1000 has a maximum receive bandwidth of 900 MHz

Figure 3.4: Operating Characteristics of DW1000

be set run simultaneously with no interference. For instance, a company wishes to track assets and personnel but on two separate systems. It is also important to note that while the IEEE 802.15.4 standard allows a UWB bandwidth of up to 1331.2 MHz, the DW1000 has a maximum receive bandwidth of only 900 MHz. The TREK1000 system used will be configured to run on channel 2 with a 16 MHz PRF for this thesis.

Ranging implementation in DecaRanging demo

In the DecaRanging demo, two UWB devices can range with each other by configuring them as tag node and anchor node respectively, using physical switches on the PCBs. The two way ranging algorithm is illustrated in Figure 3.5. Once powered up, a tag send out

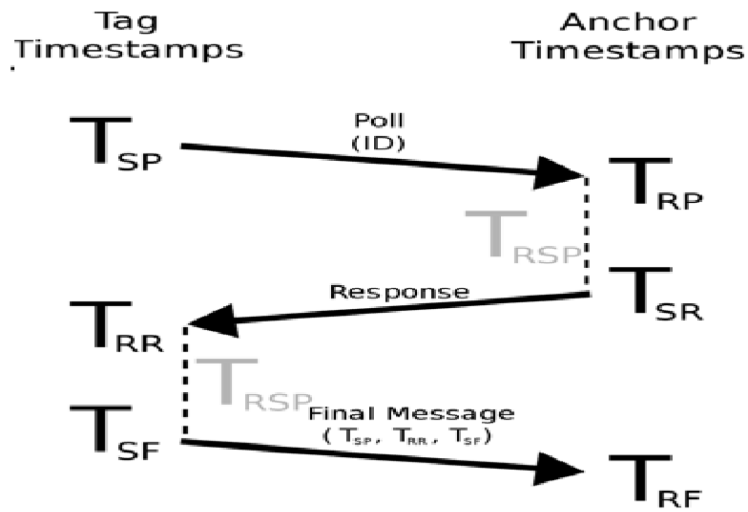

Figure 3.5: Two Way Ranging in EVB1000 [27]

broadcasts, or blinks, with one second intervals. When the anchor receives a blink, it sends back a ranging initiation message that is received by the tag, which then initiates the two-way ranging. The tag sends a poll message to the anchor that responds with a response message. The ranging is completed when the tag sends a final message containing all the relevant timestamps, followed by a sleep time of 400 ms before starting over by sending a new poll. After receiving the final message, the anchor calculates the TOF between the two nodes. This distance is affected by a range bias which needs to be compensated for, with a certain offset. After calculating the distance it is displayed on the onboard LCD screen. In demo mode, a final report message is also sent from the anchor node for displaying the same information on the tag node LCD screen.

3.3 NLOS Identification and Mitigation

It is widely known that the NLOS effect is one of the main degrader for the position estimation accuracy. Hence, NLOS identification and mitigation is another important and hot subject regarding Indoor Positioning.

No Line of Sight Situation

In NLOS situations, wireless signals that cannot go through an object, must reflect from walls or diffract from an object to reach a target node. Reflection and diffraction of a wireless signal will occur in LOS situations as well but the first signal to reach a receiver will be the direct, unobstructed path. Incoming reflected/diffracted signals entering a receiver are then discarded. In NLOS situations, the incoming received signal is a result of the reflected

Figure 3.6: LOS Scenario

and/or diffracted signal. This causes TOF, T_{prop} be larger than it should be, which causes calculated distance to be greater. In theory, in NLOS conditions, the time and distance calculated must always be greater than the time and distance in an LOS path. Since LOS is always the shortest path, there cannot be a situation where the NLOS TOA is shorter than the LOS TOA. Since a radio wave propagates at the speed of light, a one nanosecond delay equates to a measurement error of 30 cm. The size and position of an NLOS causing obstruction also affects the TOA range calculation. The size of the NLOS causing obstacle and the distance between the anchor and tag is proportional to the measurement error induced by NLOS. A $1mx1m$ obstacle will largely affect on measurement accuracy in a small room than in a large room. Figure 3.6 and 3.7 shows LOS and NLOS scenarios in general, respectively. The presence of multipath in the NLOS case raises interesting scenarios. A typical example is given in Figure 3.7. Here we can see that the direct path between the two nodes is obscured while other unobstructed paths are possible because of reflections from nearby surfaces.

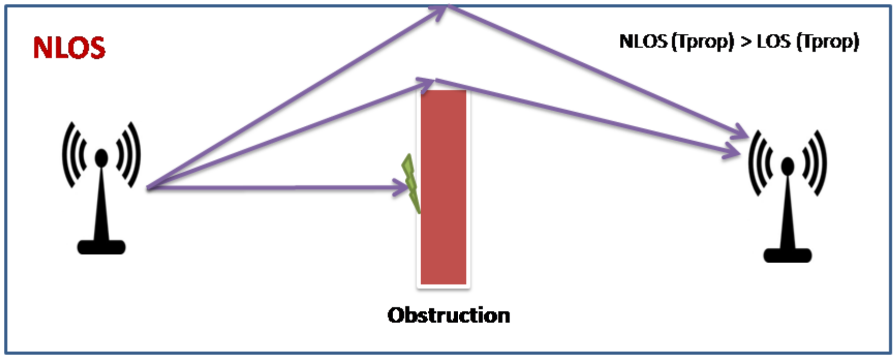

Figure 3.7: NLOS Scenario

3.3.1 Parameter Identification for LOS/NLOS

The Identification and Classification of LOS/NLOS is critical issue in this thesis. Before the mitigation of an NLOS measurement, it must be determined if the measured distance contains NLOS error. The measured distance between two points using TOA can contain significant positive error bias when NLOS occurs.The primary method for identifying LOS/NLOS is based on comparing channel parameters values of Receive signal power and Rise Time of the channel. For classification and mitigation we are incorporating the use of one more channel parameter First Path Gain. A channel measurement campaign was conducted in an laboratory environment and the measurement results confirms the validity of our rules and gave an accurate confidence level of NLOS detection. In this thesis, LOS is first identified and classified as LOS, Soft LOS, and NLOS is classified as Soft NLOS and Hard NLOS. Classification of LOS as Soft LOS, is due to signal attenuation in LOS situations as well. 'Hard' NLOS is defined as being when an obstruction severely attenuates the signal, where as 'Soft' NLOS is an obstruction that causes mild/low signal attenuation. The identification of LOS/NLOS is developed and implemented into a real time system using the DecaWave TREK1000 system and does not rely on previously sampled measurements.

Receive Signal Power Level (RSL)

The received signal power level is one of the parameters used in the identification of LOS/NLOS. It is possible to acquire an estimation of the receive signal power level. From the DW1000 documentation [20], an estimate of the RSL (in dBm) is given as,

$$RSL = 10 * log_{10} \frac{C * 2^{17}}{N^2} - A\ (dBm) \tag{3.1}$$

where C is the estimation of channel impulse response power, N is the preamble accumulation count and A is a predefined constant of 115.72 dBm for a PRF of 16 MHz or 121.74 dBm for a PRF of 64 MHz.

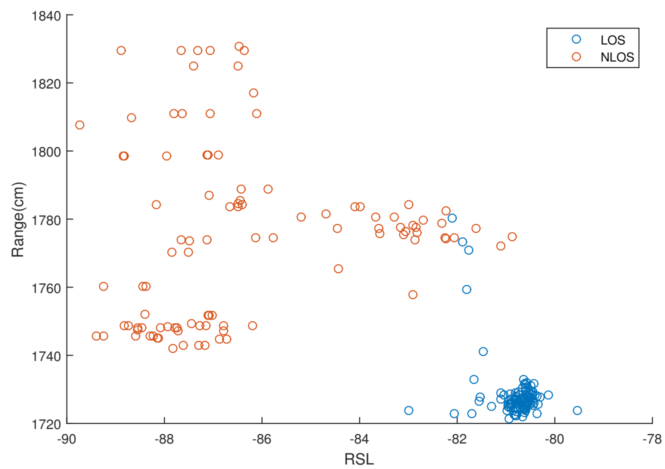

Figure 3.8: Range vs RSL

NLOS Identification by RSL

Experiments were conducted to find a relationship between NLOS and the RSL. The assumption for this experiment was that by taking the average RSL between each anchor node and the tag, the anchor experiencing NLOS would have a lower (more negative) RSL than the average between all three. Through elementary attempt, it was shown that using only RSL was not a good enough indication of whether NLOS conditions occurred or not. If one or more anchors experienced NLOS, it is hard to differentiate which ranges are actually NLOS. For example, if one anchor experiences NLOS and gives an RSL measurement higher than it should be, it is not known whether this RSL measurement is high due to the fact that the tag is either far away from the anchor or if there is an obstruction in between. One cannot confidently identify NLOS conditions using RSL as a sole parameter. It was also seen that as an anchor and tag get closer, the introduction of NLOS will cause the reported range to deviate much more severely than if the tag and anchor were farther apart. It is therefore important to keep the anchor on a much higher elevation than the tag for positioning to avoid this conflict.

Figure 3.8 compares reported range with the RSL. It is seen from the graph that the LOS RSL varied from -79.4 *dBm* to -81.1 *dBm*. The LOS reported distance deviation varies from 0 to 9 *cm* between all the experiments, proving DecaWave's LOS accuracy of $\pm 10cm$. At around -81.2 *dBm*, the distinction between LOS and NLOS is seen with the reported distance increasing significantly. It should be observed that there were also a few LOS RSL measurements that were in the NLOS RSL range but with the exception that reported distance still stayed accurate. The few LOS outlier points that were greater than -81.2 *dBm* were the first indication that RSL by itself is not a very good indicator of LOS/NLOS conditions.

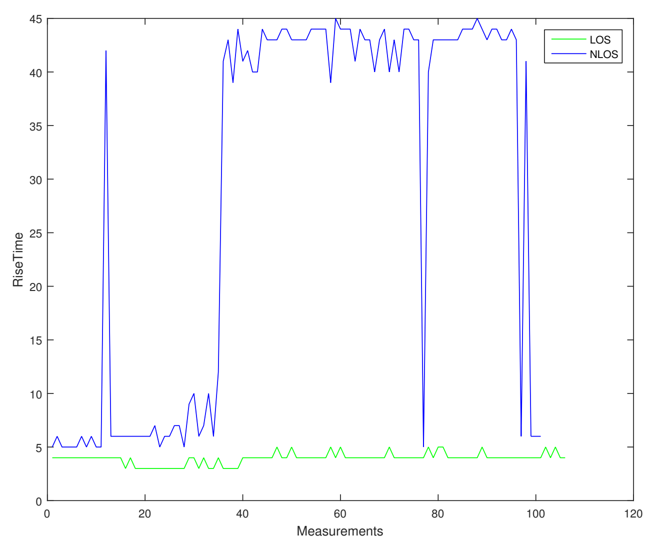

Figure 3.9: Risetime

Rise Time(RT)

Since NLOS detection using RSL was no sufficient as seen from graph and experiments, another solution has to be found to solve the problem of identifying NLOS precisely. The solution found to the NLOS identification problem was incorporating the use of the parameters called the Rise Time.

Figure 3.3, shows the received signal in the time domain with different parameters available from DW1000 for diagnostics. This allows the user to get an estimate of the First Path. First Path is the measure received signal power from the first three arriving pulses of the received signal. Peak Path is the strongest path with maximum amplitude of the received signal.

The Rise time is the time difference (in nanoseconds) between the first and peak path indexes. Multipath may report occurrence of first path and peak path at wrong indexes. Typically, the larger the difference, the more severe the NLOS condition. Rise time equation can be written as,

$$RiseTime = PeakPathIndex - FirstPathIndex \tag{3.2}$$

Figure 3.9 compares the Rise time for taken number of measurements for both LOS and NLOS. It is seen from the graph that the LOS RT is in between range from 3 to 6 nanoseconds mostly. For NLOS, RT is fluctuating after 6 nanoseconds, not giving a range estimation for RT related to NLOS but the distinction between LOS and NLOS is seen with the reported distance increasing significantly with RT.

First Path Gain (FPGain)

First Path Gain is an estimate of measure of first path to the Peak Path for that received signal.

$$FirstPathGain = FirstPath(F1, F2,\ or\ F3)/PeakPath \tag{3.3}$$

where $F1, F2, F3$ are first three arriving pulses amplitude points.

For LOS conditions, Peak Path is usually one of the three arriving pulses of the received signal i.e. $F1$, $F2$ or $F3$. For NLOS conditions, due to signal reflection or diffraction, these path amplitudes vary and they may report below noise threshold and we get the wrong first

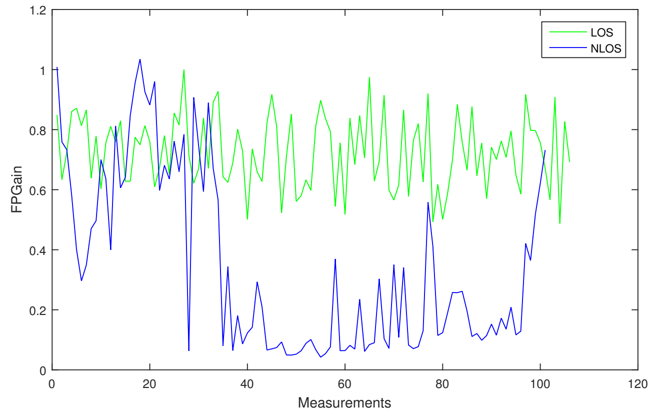

Figure 3.10: FPGain

path or peak path values. Values of First Path Gain varies from 0.05 up to 1 for different LOS/NLOS conditions.

Figure 3.10 compares First Path Gain value for LOS and NLOS with number of measurement. FPGain values for LOS are mostly closer to the value 1. While for NLOS, they are spread out all over the span of graph, not giving certain values for comparison. Thus, We are considering different FPGain values for different RSL and Rise Time.

3.3.2 Rules Formation and Validation for NLOS Identification and Classification

All the parameters needed for calculating RSL and Rise Time can be readily accessed from the registers on the DW1000 transceiver chip. With some pre-requisite, these parameters would allow for better accuracy in identifying NLOS. These pre-requisite are solely based on the following observations from experiments:

1. In NLOS conditions, signals are considerably more attenuated and have smaller energy and amplitude due to reflections or obstructions,

2. In LOS conditions, the strongest path of the signal typically corresponds to the first path, while in NLOS conditions weak components typically precede the strongest path, resulting in a longer rise time

Figure 3.11 and 3.12 shows the CIR graph for LOS and NLOS. In the presence of a signal, the impulse response shows the magnitude of the energy received along the direct path and each of the multipaths that follows it. The first path is clearly visible and is the strongest signal received for LOS. It is seen visually that the NLOS CIR graph has a large amount of noise, and the first incoming pulse has amplitude similar to the rest of the incoming pulses. Both figures 3.11 and 3.12 depicts two waveforms received in the LOS and NLOS condition supporting our observations.

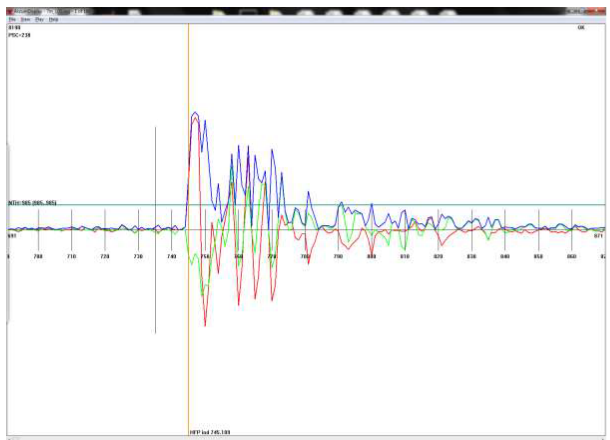

Figure 3.11: CIR for LOS

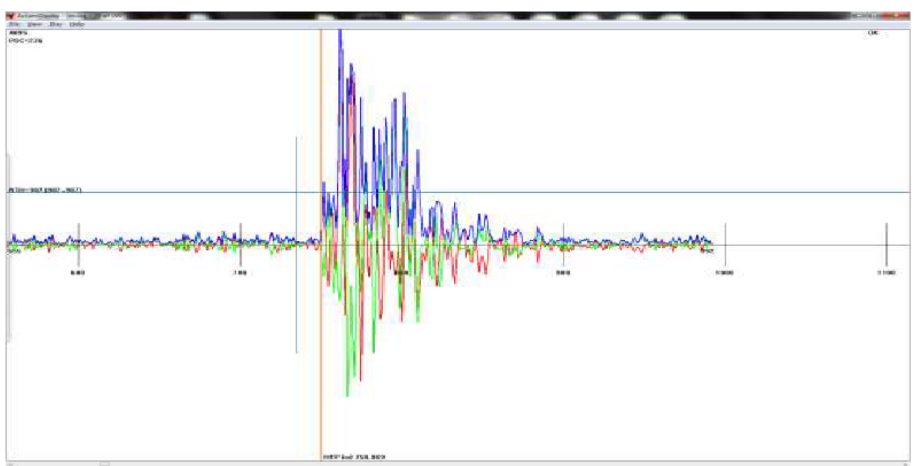

Figure 3.12: CIR for NLOS

Proposed Rules Classifier

By combining both RSL and RT, the identification of NLOS, along with the severity of it was able to be obtained from the developed system. The method used to identify NLOS was defining Rules with certain power level and RT values based on simulations and testing in real time. The proposed Rules Classifier are,

Rule 1: $RSL >= -81.1 \implies LOS$

$RSL < -81.1 \implies NLOS$

Rule 2: $RT <= 6 \implies LOS$

$RT > 6 \implies NLOS$

In this research, the experiments use three anchors and one tag to perform simulations and practical implementations to demonstrate the validity and practicality of the proposed Identification/Classification Algorithm. Simulations results are provided in chapter 4. The identification and classification algorithm is given below:

Algorithm 1: Identification/Classification Algorithm

```
if RSL ≥ −81.1 then
    if RT ≤ 4 then
        LOS
    end if
    if 4 < RT ≤ 6 then
        Soft LOS
    end if
else
    if RSL ≥ −84.1 then
        if RT < 6 then
            Soft NLOS
        end if
        if 6 ≤ RT < 12 then
            Hard NLOS
        end if
        if RT ≥ 12 then
            Hard NLOS
        end if
    end if
end if
```

As seen from the algorithm we are classifying LOS ranges as LOS and Soft LOS, and NLOS range is classified as Soft NLOS and Hard NLOS. The Classification justifies signal attenuation in LOS situations as well. There are instances where the first path signal may have a low amplitude due to NLOS and can be mistaken as noise by the DW1000. To mitigate this, a detection threshold is set as seen in Figure 3.13. Setting the threshold cutoff too high will cause the first path to be ignored and if the cutoff is set too low, it can cause noise spikes to be detected. For this thesis, the default threshold values set by the manufacturer were used. Threshold can be set upon different applications needs.

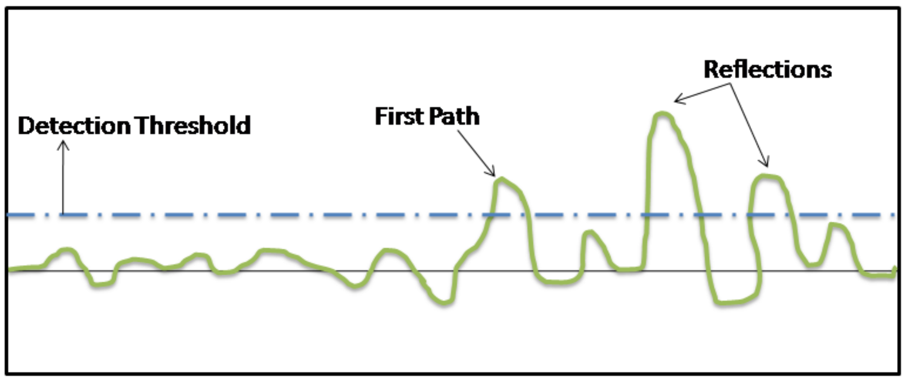

Figure 3.13: Received Signal Interpretation

3.4 NLOS Mitigation

The proposed mitigation algorithm will mitigate the calculated range between a tag and an anchor, which results in an improvement in of a tag's coordinates after range processing through trilateration. The algorithm requires the identification of LOS/NLOS for error measurements between the tag and all anchor nodes. Once an anchor is identified as being NLOS, the algorithm will mitigate the NLOS range measurement, consequentially also mitigating the position of the target under NLOS. Combination of the identification and classification rules with different FPGain values forming Master Rules for NLOS identification, classification and mitigation will correct the range difference because of signal attenuation.

Anchors are placed to form a triangular shape. Within the boundaries of anchor perimeter formed by the three anchors, an NLOS reported range can be mitigated as long as the parameters values for the algorithm are met. The area enclosed by the anchors is defined as in bound area. If tag is outside of this area mitigation may also take place but the error or range reported by mitigation algorithm may still not be accurate. To make it more accurate for larger area we can increase the number of anchors or possible approach are suggested in Future Work.

As discussed earlier, FPGain values do not distinguish LOS/NLOS very accurately. So we are evaluating different FPGain values for different RSL and RT values and measuring the error and correcting the range. FPGain values are very critical for measuring the error.

A MATLAB and python script for Rules is written and applied to range reported by tag plugged to the mobile vehicle for simulation and in real time implementation. The mitigation algorithm is given below. The algorithm works in sequence with checking different parameters. In first step it will check the received signal power level value, in second step it will check the corresponding Rise time value and in last it will check FPGain to return an output corrected range based on given inputs. A simulation of the mitigation algorithm is

Algorithm 2: Mitigation Algorithm

```
if CheckRSL then
    if CheckRT then
        if CheckFPGain then
            Mitigated Ranges = Ranges - Error;
            return Mitigated Ranges
        end
    end
end
```

developed and the results are provided. As NLOS severity increases, the mitigated position becomes more accurate in comparison to the position using the raw range reported.

3.5 Position Determination

The ultimate goal of providing a reliable channel condition estimation/detection algorithm is to facilitate the localization algorithm design for improved accuracy. Ranging information is exchanged between tag and anchor nodes in order to achieve localization for the mobile vehicle.

Trilateration

After mitigation of ranges, mitigated ranges are processed in Trilateration algorithm to get the more accurate coordinates of the mobile vehicle.

Trilateration is a method to determine the relative coordinates of an object using ranges to a target node from at least three other reference nodes whose coordinates are known. Trilateration algorithm uses the TOF which makes use of the relation given in equation 3.4 to measure the Euclidean distance between two nodes,

$$Distance(d) = Speed(C) * Time(T) \tag{3.4}$$

Since radio signals travel with the speed of light, which is a known constant measured to exactly 299792458 m/s, the distance between a transmitter and a receiver can be calculated after measuring the TOF. A MATLAB and Python script of trilateration was used to identify the tags position once all three ranges were acquired.

By identifying and mitigating the biased ranges and calculating the final location can be combined into one full algorithm. The pseudo code for this algorithm is shown below.

Algorithm 3: Location Algorithm

```
counter = 0;
MeasureRanges();
Mitigation();
Trilateration();
counter++;
```

3.5.1 Smoothing Of Co-ordinates

However, the issue experienced was the measurement noise of the UWB tag when stationary. Initially, a single threshold parameter was set to not update the current position unless the new position received from the UWB tag was larger than the threshold. Another method attempted was calculating the average of the received measurements over 1 second, but this just resulted in delaying the time the next position would change to every 1 second rather than 3.5 times a second.

In this way, the proposed approach was to utilize a moving window average with a desired threshold distance. By utilizing a moving window average, the output frequency of the data can continue to remain at 3.5 Hz and the only delay would be the initial time it takes to fill the window. Calculating the average of the window also helps to mitigate some outliers during operation. Additionally, the use of the threshold distance helps reduce the measurement noise by not accepting small position changes. Therefore, the average of the window would not be changed unless the estimation values are large changes.

Chapter 4

Simulation And Implementation

4.1 System Setup

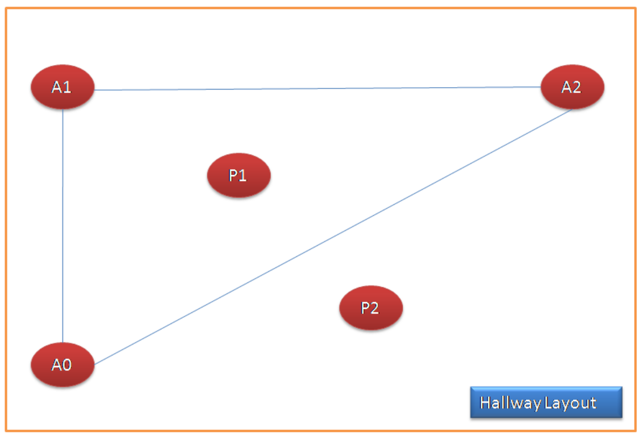

Figure 4.1: System Setup

Three UWB anchors were set up in an triangle formation at height in the laboratory area of Wireless Communication And Information Processing at the University. The distance between each anchor node was about 3 m. The UWB tag node connected to BBB was placed inside and outside of the triangle. A layout of the setup is shown in Figure 4.1. P1 and P2 are the two testing points where the tag was placed. Anchor 0 is placed at the origin and the other anchors are placed to the left and above the origin. A sheet of metal was the obstacle placed in between the anchor/tag to imitate NLOS. The obstacle was moved between each anchor/tag. NLOS was created for one anchor at a time with the tag in the same position by using a 0.48 m x 0.44 m Styrofoam board coated with aluminum

Table 4.1: Position Values

Parameter	**Value**
Anchor 0	(0 cm, 78 cm)
Anchor 1	(0 cm, 359.4 cm)
Anchor 2	(370 cm, 359.4 cm)
Position 1 (95%)	(137.24 cm, 280.78 m)
Position 2 (95%)	(206.3 cm, 235 cm)

foil. The aluminum foil would act as a metallic layer to attenuate the UWB signal and prevent it from passing through the Styrofoam board. The aluminum foil board was placed about in between the specific anchor and tag that were to simulate artificial NLOS. An illustration of how NLOS was created artificially by using an aluminum foil covered board is shown in Figure 4.2. Anchors' and tag's position values are provided in Table 4.1. The actual position of the tag was measured using a laser distance meter with a 95% confidence interval.

Figure 4.2: Artificial NLOS creation in Hallway

4.1.1 Test Procedure

Real world data was first gathered and stored using the TREK1000 equipment. The anchors were arranged at fixed positions in the hallway. The tag was moved around to two positions in the hallway as well. The experiments performed were uniform for all test conditions. For each test, around 40 ranging measurements were taken. A full test would be equivalent to an aggregate of 480 range measurements for each position and a total of 960 for both positions. For each stationary tag position conducted test scenarios, are as shown in Table 4.2.

Table 4.2: Test Scenarios

LOS	A0 NLOS	A1 NLOS	A2 NLOS
x	x	x	x

4.2 Simulation Results from MATLAB

The mitigation algorithm was developed and tested in MATLAB. The simulations included getting real data as .CSV files from the TREK1000 and the designing of the mitigation algorithm to apply to compare the mitigated result to the NLOS result and the true range of the tag. The method to compare the true range of the tag with the mitigated result was done by taking the difference between the true and mitigated range.

After the TREK1000 system collected the data, it was saved to a .CSV file. Each of the three test scenarios has an individual .CSV file so that data could be isolated and analyzed individually. Then a script was created in MATLAB for each NLOS scenario that could occur at an anchor. In each of the LOS test scenarios per each tag point, 40 ranging measurements and the associated calculated coordinates were taken and averaged to give a reference for LOS conditions.

The four input variables for the LOS and NLOS data files were the uncorrected ranges, Received Power Level (RSL), Rise Time (RT) and First Path Gain (FPGain) and were loaded into MATLAB. After the NLOS ranges were loaded into MATLAB, the mitigation algorithm was run for each range and the mitigated range would then replace the NLOS range. MATLAB simulations has been explained in more details in below subsections.

4.2.1 Range Mitigation Results

The range mitigation algorithm was tested in MATLAB using the collected experimental range measurements to observe the effect of mitigation. Table 4.3 shows a comparison of the True, NLOS and Mitigated range measurements as R_True, R_NLOS and R_Miti, respectively for the each position in the hallway. From Table 4.3, it is observed that the mitigation algorithm provides a closer range estimate in reference to the true range. From Table 4.3, it is observed that the mitigated range has a lower diversion compared to the NLOS range measurements. Diversion of range measurements also occur in perfect LOS conditions using the TREK1000 system. From the simulations, it can be proven that NLOS range accuracy of ± 15 *cm* from the True range is achieved.

Table 4.3: Range Mitigation Results

		R_True (cm)	R_NLOS (cm)	R_Miti (cm)
Position 1	R_0	263.5	312.075	298.4
	R_1	200.3	235.3382	217.6911
	R_2	263.7	305.251	303.5
Position 2	R_0	270.05	305.32	287.96
	R_1	251.2	304.380	302.73
	R_2	222.4	285.478	270.47

4.3 Implementation

This section of the thesis focuses on the practical implementation aspect of the research. The main focus of this thesis is to identify NLOS situations and to mitigate NLOS measurements and hence accurate the position of the object. In order to mitigate a range, it must first be determined that a range needs to be mitigated in the first place.

4.3.1 Accessing Registers of DW1000 for Obtaining required Parameters

Most of the parameters needed to design the Rules were readily available from the

REG:10:00 – RX_FINFO – RX Frame Information																															
31	30	29	28	27	26	25	24	23	22	21	20	19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
RXPACC												RXPSR		RXPRF		RNG	RXBR		RXNSPL		-	RXFLE			RXFLEN						
0												0		0		0	0		0		0	0			0						

Figure 4.3: RX_FINFO register of DW1000

REG:12:00 – RX_FQUAL – Rx Frame Quality Information (Octets 0 to 3, 2x16-bit values)																															
31	30	29	28	27	26	25	24	23	22	21	20	19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
FP_AMPL2																STD_NOISE															
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

REG:12:04 – RX_FQUAL – Rx Frame Quality Information (Octets 4 to 7, 2x16-bit values)																															
31	30	29	28	27	26	25	24	23	22	21	20	19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
CIR_PWR																PP_AMPL3															
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 4.4: RX_FQUAL register of DW1000

EVB1000 boards. But to access them as well, understanding of how this devices are made and how they work is an challenging task. In depth knowledge of this device to work as required by the application is achieved.

For retrieving the power level of the signal, the variables F1, F2, F3, C and N needed to be recovered from the registers of the DW1000 chip. Figures 4.3, 4.5 and 4.4 below shows an example of these registers. From Registers RX_FINFO and RX_FQUAL, F2 (FP_AMP2), F3 (PP_AMP3), N (RX_PACC) and C (CIR_PWR) are extracted [20]. The function used to recover these values was,

$$dwt\_read16bitoffsetreg(int regFileID, int regOffset) \tag{4.1}$$

which is the part of the Decawave's Source Code. In total there was three sets of these variables; one set for each anchor/tag combination. These values are calculated from each anchor/tag that is being used. It should be noted that to recover N, a bitwise mask of 0xFFF was applied to the register 0x10 and then shifted to the right by 32 bits. First Path Index (FP_INDEX) is available from register RX_TIME. To obtain Peak Path Index for FPGain,

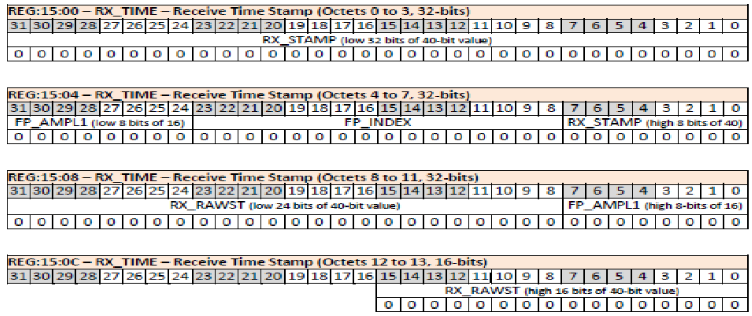

Figure 4.5: RX_TIME register of DW1000

Accumulator Register of the DW1000 register was read which holds the accumulated channel impulse response data. To read the Accumulator register, function used was,

$$dwt\_readaccdata(uint8 * buffer, uint16len, uint16accOffset) \tag{4.2}$$

available from Decawave. Only values till Peak Path were accessed and reported to the tag. Whole accumulator reading with TREK1000 system is very time consuming and not required for application. All of the required variables are extracted from registers like these.

4.3.2 Mitigation Algorithm Implementation

The mitigation algorithm was also implemented on the Beagle bone Black to which Tag is connected through USB. Once range is available from Tag, the mitigation algorithm would be run. The algorithm will also show which anchor(s) are experiencing NLOS based on severity. The classifications was chosen based on testing with NLOS causing objects (including humans) and how they impacted the ranging result. NLOS classification is used as a parameter in the mitigation algorithms for the approximation of the error. Once the range is mitigated, they will be passed on to the Trilateration function for calculating the location value.

4.3.3 NLOS Identification and Classification Results

For each tag position, NLOS was artificially created by placing an object between each anchor and the tag, with only one NLOS anchor at a time. The parameter values used to make the Rules for each anchor, was taken and mitigation algorithm ran and results tabled in Tables 4.4, 4.5 and 4.6. From the Tables, it was again observed that RSL does not vary

Table 4.4: Anchor 0 parameters when A0 is NLOS

A0 NLOS						
		RSL	RT	FPGain	LOS/NLOS	Error (cm)
Position 1	A0	-81.73	2	0.8540	Soft NLOS	20
	A1	-78.253	3	0.9097	LOS	-4
	A2	-77.71	3	0.9384	LOS	-3
Position 2	A0	-84.021	12	0.7616	Hard NLOS	15
	A1	-79.255	3	0.7595	LOS	-3
	A2	-80.873	3	0.6998	LOS	-8

much under NLOS conditions. This further strengthens the preliminary RSL experiments performed. On the other hand, the RT and FPGain parameters varied greatly for an anchor experiencing NLOS.

As the Received Power is high and the RT is low $(2-4)$ for LOS conditions the error is low (more negative). For medium received power, if the RT is low $(5-10)$, error is medium $(6-18cm)$. As the RT increases, the error becomes low to some point due to the fact that early detection of first path after synchronization is possible. However, as the RT increases, the detection may be false detection because shortest path may be buried under the threshold and increasing the error.

For low Received Power, as the received power decreases the detection of first path is false and the error will be very high (around 1 m) for very low RT. As the RT increases, the error will increases, too.

4.3.4 Position Mitigation Results

Figure 4.6, shows the position mitigation results for the Position P1 when Anchor 0 is experiencing NLOS. From Tables and Figure 4.6 it can be proved that, using the evaluated RSL, RT and FPGain values for the Rules for the NLOS identification and mitigation of ranges, an accurate LOS/NLOS identification and mitigation of ranges was achieved and

Table 4.5: Anchor 1 parameters when A1 is NLOS

A1 NLOS						
		RSL	RT	FPGain	LOS/NLOS	Error (cm)
Position 1	A0	-78.86	3	0.8413	LOS	-4
	A1	-81.44	22	0.6031	Hard NLOS	13
	A2	-78.122	4	0.5413	LOS	-2
Position 2	A0	-81.010	3	0.9214	LOS	-4
	A1	-85.474	3	0.7099	Soft NLOS	20
	A2	-81.01	3	0.9682	LOS	-4

Table 4.6: Anchor 2 parameters when A2 is NLOS

A2 NLOS						
		RSL	RT	FPGain	LOS/NLOS	Error (cm)
Position 1	A0	-77.251	3	0.8420	LOS	-4
	A1	-77.383	6	0.7814	Soft LOS	4
	A2	-81.587	5	0.9945	Soft NLOS	-6
Position 2	A0	-80.795	3	0.8445	LOS	-4
	A1	-82.576	5	0.7666	Soft NLOS	18
	A2	-85.318	57	0.5694	Hard NLOS	120

the accuracy of position was also achieved. The detection and mitigation of NLOS using the TREK1000 hardware was successful.

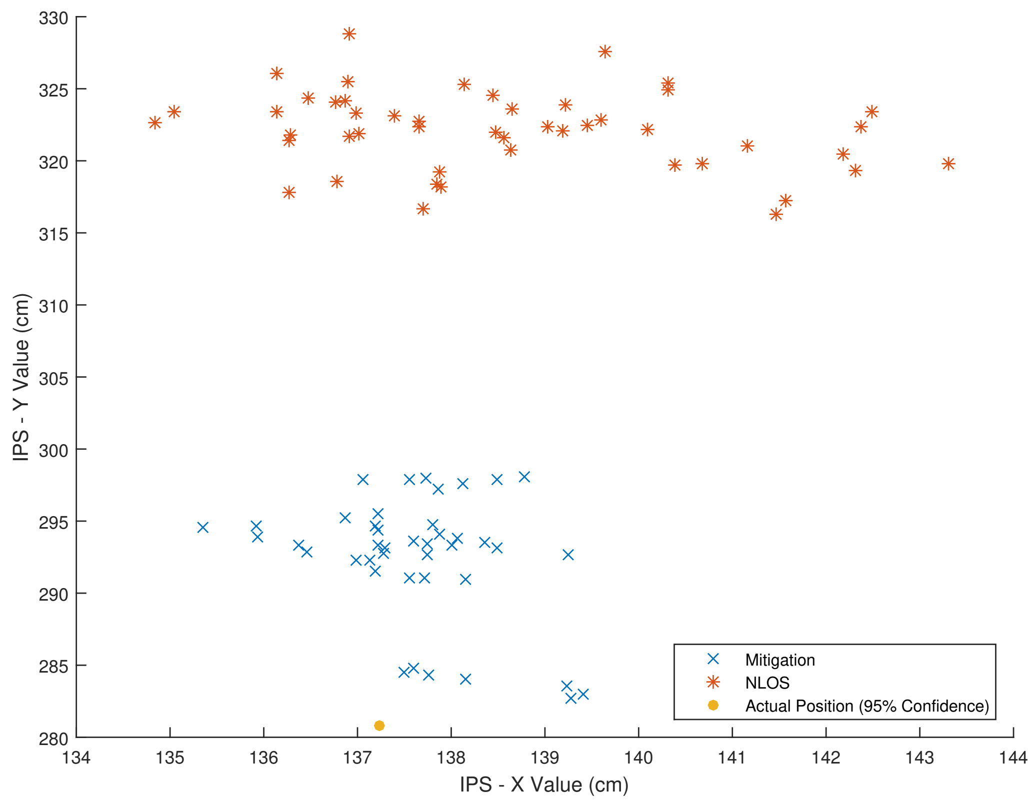

Figure 4.6: Position Mitigation Results

Chapter 5

Conclusions & Future Work

5.1 Conclusions

UWB technology allows precision wireless localization and therefore provides a viable technology for enabling reliable and robust location based services in indoor applications. The results of this thesis shows that UWB technology allows for indoor ranging with centimeter precision. A major challenge facing distance/range estimation is the bias presented in NLOS channels and as a result, correctly identifying such channel condition is critical to the overall localization performance. This thesis presents a low cost, low complexity channel condition estimation algorithm which utilizes channel parameters. The validity of our algorithm is supported by the channel measurement conducted in an indoor environment. Further, the robustness of our rules has been confirmed with both measurement and simulation data. Conclusions drawn are,

- UWB based IPS is a big and exciting research area
- Rules are derived from parameters which are extracted from channel impulse response of IR-UWB
- Rule based classification do not require intensive hardware resources as only simple comparison of parameters involved
- NLOS range accuracy of ± 15 *cm* from the True range
- A system developed under $2000

5.2 Future Work

There is much prospective work in UWB based indoor positioning utilizing time of arrival as this issue is relatively new. To start, future work may specifically include an extension of the work covered in this thesis. NLOS mitigation algorithm created is for discrete values, an algorithm for linear values can be developed with the Fuzzy system. Different areas of future work may include expansion of the development in this thesis to be able to cover numerous rooms and investigation on different materials and temperatures in a room may influence indoor positioning on the UWB spectrum.

In the work examined in this thesis, at once only a single room was used for experiments. The capacity to cover all the area in a warehouse, with many sets of anchors will be demanding. As a mobile vehicle moves from one place to another place, the capacity for an anchor to handoff the tag to another rooms anchor is critical. In the event that a room contains multiple metallic objects, there might be more multipath and the performance of an IPS will vary compared to a room with no metallic items. The impact of temperature on UWB indoor positioning may likewise be a great area of future work as indoor environments may not be climate controlled and may be a high temperature in summer or very low temperature in the winter. This may cause items inside of a room to show different attenuation and reflection characteristic, which may affect indoor positioning system.

The fusion of UWB with any other positioning system results in good accuracy levels as reviewed in literature review. The fusion of UWB based IPS with INS system is an ongoing research at the WICIP lab of University of Windsor.

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